Effects of soil dust episodes and mixed fuel sources on source apportionment of PM10 particles in Kuopio, Finland

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Abstract

A receptor modeling study was carried out in Kuopio, Finland, between January and April 1994. Near the center of town, the daily mean concentrations were measured for PM10, sulphur dioxide, carbon monoxide and Black Smoke. Elemental concentrations of PM10 samples for 38 days were analyzed by ICP-MS. The main sources and their contributions to the measured concentrations of PM10 particles were solved by receptor modeling using a factor analysis-multiple linear regression (FA-MLR) model. Because a dust episode was very strong during two sampling days, the FA analysis was strongly influenced by this episode and did not give main factors. The factor analysis, when the two episode days were omitted, gave credible factors related to the sources in the study area. The four major sources and their estimated contributions to the average PM10 concentration of 27.2 μg m^{-3} were: soil and street dust 46–48%, heavy fuel oil burning 12–18%, traffic exhaust 10–14%, wood burning ca. 11% and unidentified sources 15–25%. However, during spring dust episode days, with maximum PM10 concentration of 150 μg m^{-3}, the main source of PM10 was soil. © 1999 Elsevier Science Ltd. All rights reserved.

Keywords: Receptor modeling; FA-MLR; Dust episode; Particulate matter; PM10

1. Introduction

Receptor modeling has been applied in the study of particulate air pollution from the early 1970s. The starting point of receptor modeling is reversed compared to dispersion modeling. The main sources of particulate matter are solved using chemical composition of ambient air particles at the measuring site and chemical characteristics of source emissions. Traditionally receptor modeling methods have been divided into two main groups; chemical mass balance (CMB) and multivariate methods. CMB uses chemical composition data of particles both from the measuring site and from the sources. In principle, CMB can calculate the proportions of all known sources from one ambient air sample. Multivariate methods, like target transformation factor analysis (TTFA) and factor analysis-multiple linear regression (FA-MLR), normally use only chemical composition data of ambient air particles, and solve both the number and chemical characteristic of sources and their contribution to the measured concentrations. However, methods require dozens of ambient air samples, because source apportionment is based on statistical methods. Complete description of these receptor modeling techniques have

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been presented by Henry et al. (1984), Gordon (1988) and Hopke (1991). One of the newest and most promising techniques is the use of neural networks. This method is still under development and the first receptor modeling results have been published by Wienke and Hopke (1994).

The purpose of this study was to identify the main sources of inhalable particulates (PM10) and their contribution to the measured PM10 concentrations in sampling sites where co-combustion were used in energy production and where resuspended dust episodes can occur. Receptor modeling was done simultaneously with the health study Pollution Effect on Asthmatic Children in Europe (PEACE), the purpose of which was to determine the effects of short-term changes of air pollutants on the respiratory health of children with chronic respiratory symptoms. Results of PM10 particles' health effects on the basis of the Finnish part of the PEACE have been published by Timonen and Pekkanen (1997).

2. Materials and methods

2.1. Sampling site and emission sources

Air pollution measurements were carried out between 31 January and 30 April 1994 and the measuring site was located near the center of Kuopio (Fig. 1). The city of Kuopio (62°53′N27°38′E, 100 a.s.l.) has 85 000 inhabitants and is situated in the middle of the lake region of Finland. The sampling site was located at least 50 m from any of the surrounding main streets, in an area surrounded by a small number of buildings of 3–5 floors. The average daily traffic density on the surrounding streets was calculated to be about 14 000 cars per 24 h on weekdays, 11 000 cars per 24 h on Saturdays and 9000 cars per 24 h on Sundays.

The only other major source of pollution besides traffic was a peat-fired power station of 350 MW equipped with
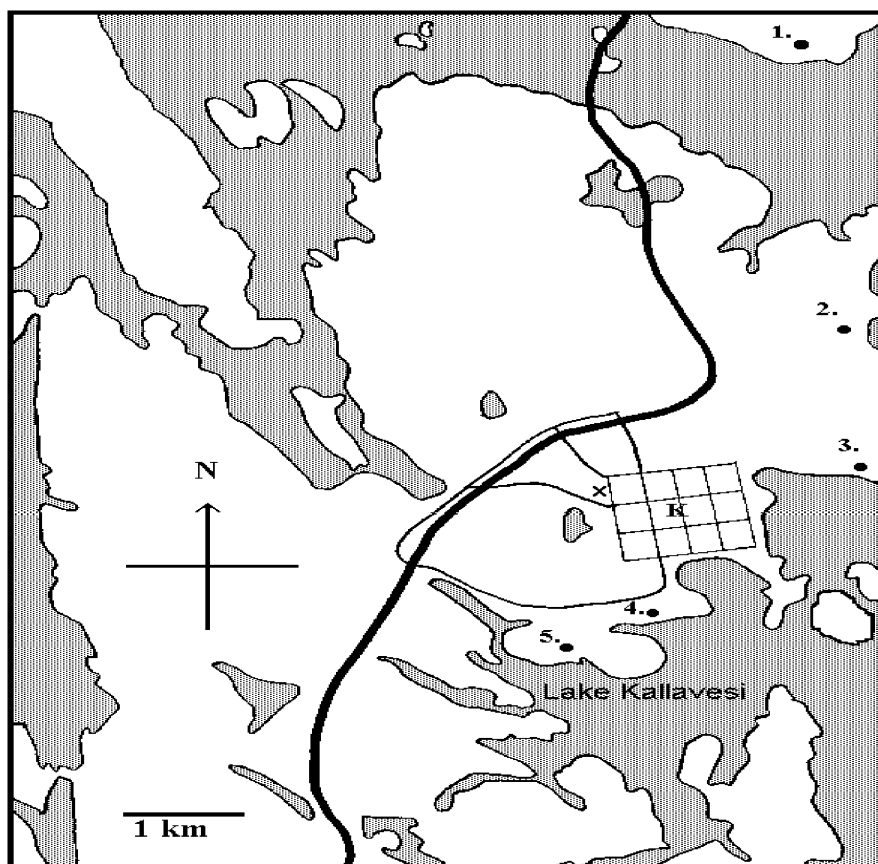

Fig. 1. Point sources of airborne particles in the Kuopio area and the most important streets in the town. In map: 1: pulp mill; 2: industrial power plant; 3: chipboard factory; 4: peat-fired power station 5: industrial power plant; X: measurement site; and K: town center.

an electrostatic precipitator located 1.5 km southeast of the sampling site. Over 80% of residential heating systems in the city are connected to this power station via the municipal district heating system. Some small industrial power plants using residual oil as their fuel were located at distances of 1.5–3 km from the site (Fig. 1).

2.2. Field measurements

Inhalable particles (PM10) were measured using a Harvard impactor (Air Diagnostic and Engineering Inc.) with a sampling flow of 10 l/min. The impactor is similar to the one described by Marple et al. (1987), except that it has only one impaction stage. Air flow was controlled by a critical orifice and real sampling flow was measured before and after each sampling period using a rotameter. The sampling period was 24 h, covering the period from noon to noon ($\pm$ 1 h). Particles were collected to Andersen 2 μm Teflon filters. A microbalance (Sartorius M3P) was used to weigh the filters before and after sample collecting, and the static charge of filters was removed before each weighing using ^{241}Am alpha source. Filters were stored at constant humidity and temperature at least 24 h before weighing and were transported to the measuring site using glass petri dishes. The quality of filter handling was determined by collecting 10 field blank samples, and the quality of weighing was controlled by a constant mass filter. Sulfur dioxide was measured by fluorescence analyzer (Monitor Labs Inc Model 8850) and carbon monoxide by a non-dispersive infrared spectrometer (Thermo Environmental Instruments Inc Model 48). Mean concentrations for 24 h were calculated from one-minute mean concentrations. Mean black smoke concentrations for 24 h were measured simultaneously with inhalable particles. Samples were taken onto Whatman 1 filters and measuring of reflectance was carried out in the University of Wageningen, the Netherlands (Brunekreef, 1993). The quality was taken into account by collecting 10 field blank samples. Meteorological parameters (wind speed and wind direction and temperature) were measured in the municipal weather station, 1 km south from the measuring site.

2.3. Chemical analyses

The measuring period covered three months and 88 filter samples. Because of limited financial resources, only 38 filters were analyzed. These filters were chosen from whole measuring period, ensuring that both high and low concentration days were represented. Elemental concentrations of these filters were analyzed by ICP-MS method (SCIEX ELAN 5000) in the laboratory of Geological Survey of Finland. Particles were extracted from filters with the mix of HF (0.5 ml, 40%), HNO$_3$ (1.5 ml, 60%) and ultrapure water (8 ml). Total extraction time was

four days. The complete description of the analysis method has been published by Jalkanen et al. (1996). The quality of analyses was ensured by analyzing certified standard material (National Bureau of Standards, Standard Reference Material 1648, Urban Particulate Matter). Thirty-one elements were analyzed but only 18 were sufficiently above the limit of detection and are reported here.

2.4. Selection of modeling method

Because a detailed source information was not available, the only possibility was use of multivariate methods. Factor analysis-multiple linear regression (FA-MLR) was selected as a method because the airshed of Kuopio is not very complex due to light industrialization. In addition to that, FA-MLR is based on traditional statistical methods, and it is simple to use with common statistical software packages. This method was first presented by Kleinmann et al. (1980) and a modified version later by Morandi et al. (1987). It uses factor analysis to identify the number of sources and to choose an independent marker element for each source. After that, multiple linear regression is carried out using marker element as an independent and total particle concentration (e.g. PM10) as a dependent variable. The basic equation of FA-MLR is

$$Y = \sum_{i=1}^{p} R_i X_i + C, \tag{1}$$

where Y is the dependent variable concentration (in this case PM10), X_i is the concentration of tracer of each source, R_i is the regression coefficient of each tracer, p is the number of sources and tracers, and C is a constant (proportion of particles from unidentified sources).

Equation (1) requires that every source has a unique tracer. However, according to Morandi et al. (1987) it is possible to calculate a secondary tracer C' for a source without unique tracer, if all sources releasing tracer X_i are known. First, the atmospheric concentration of X_i is the sum of its individual source contributions, and can be calculated as follows:

$$X_i = \sum_{i-1}^{p-1} R_i U_i + C', \tag{2}$$

where p is the number of sources releasing X_i, U_i is the atmospheric concentration of the unique tracers of sources which also release X_i, R'_i is the regression coefficient for the unique tracers of sources contributing to X_i, and C' is the fraction of X_i which is associated with sources without a unique tracer. Next, C' is solved from the equation, and it can be used as a unique tracer in the final apportionment equation (Eq. (1)). All statistical analyses were done using SPSS PC + 5.0 software.

Table 1
Statistics for the measured variables in Kuopio in 1994 (38 samples, averaging time 24 h)

Variable	Minimum	Maximum	Median	Mean	Standard deviation
PM10 ($n = 38$) ($\mu g\,m^{-3}$)	4.7	158	19.3	27.2	29.2
PM10 ($n = 36$) ($\mu g\,m^{-3}$)	4.7	61.6	18.7	21.2	13.0
CO ($mg\,m^{-3}$)	0.14	2.8	0.51	0.63	0.55
SO_2 ($\mu g\,m^{-3}$)	0.13	32.4	3.6	6.6	0.74
Black smoke ($\mu g\,m^{-3}$)	1.6	57.0	12.8	15.1	12.0
Temperature (°C)	− 21.6	9.8	− 5.4	− 5.0	7.7
Wind speed ($m\,s^{-1}$)	1.5	8.0	3.4	4.0	1.9

Table 2
Statistics for the elemental concentrations in Kuopio in 1994 (38 samples, averaging time 24 h)

Element $n = 38$	Minimum ($ng\,m^{-3}$)	Maximum ($ng\,m^{-3}$)	Median ($ng\,m^{-3}$)	Mean ($ng\,m^{-3}$)	Standard deviation ($ng\,m^{-3}$)	Number of samples under detection limit
Al	2.8	10 200	300	940	2000	0
Ba	< 1	118	4.4	12	23	5
Ca	28	6500	300	650	1200	0
Cr	< 2	14	1.6	2.4	2.9	3
Cu	3.2	124	21	30	25	0
Fe	30	8900	300	840	1700	0
K	< 70	2200	120	250	430	2
Li	0.4	8.1	4.3	4.5	1.9	0
Mg	11	3200	120	320	630	0
Mn	< 0.2	140	13	21	27	2
Na	15	2600	240	390	510	0
Ni	0.5	9.2	3	3.3	1.9	0
Pb	0.3	32	8.4	10	6.5	0
Si	< 70	26 300	770	2900	5700	6
Sr	0.4	58	2	5.7	11	0
Ti	< 10	750	18	64	150	10
V	0.5	25	4	5.8	5.1	0
Zn	< 2	60	14	18	16	5

3. Results

3.1. Measured data

The statistics of the measured variables are presented in Table 1. The means, medians, standard deviations, maximums and minimums and number of samples under the detection limit in chemical analysis are presented in Table 2. PM10 concentrations during 38 days of data varied between 5 and 158 $\mu g\,m^{-3}$ with a mean of 27.2 $\mu g\,m^{-3}$. Fig. 2 shows the locations and concentrations of those days compared to the complete 88 days of data. Remarkable in this figure are the very high PM10 concentrations between 10 and 13 April. This type of dust episodes appear every spring when the snow and ice melt away and the ground and the streets become dry. Depos-ited particles from combustion processes and the dust formed from asphalt and street sand by studded tires are resuspended by wind and traffic into the ambient air. As a consequence, most elements reach their maximum con-centrations during these episodes and also the national air quality guidelines of particulate matter are often ex-ceeded.

3.2. Factor analysis

Before analysis, all concentrations under detection limit were replaced by zero. According to Morandi et al. (1987) replacements less than 15% had no notable effect on the results of qualitative factor analysis. The amount of replacements was not more than 13% for elements included in the final analysis (Table 2). The use of
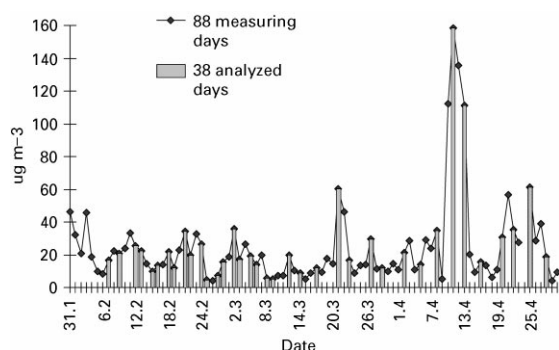
Fig. 2. Results of PM10 measurements in Kuopio in 1994.

multivariate methods requires a minimum number of samples, which can be calculated using a "rule of thumb" equation when the number of variables is known (Henry et al., 1984). Because the number of samples was 38, the maximum number of variables according to Henrys equation could be 13. Selection of variables to the analysis was done on the basis of preliminary factor analysis and literature (Hopke, 1991; Huang, 1994). For instance, there were several alternative markers for soil dust which were loaded only in the soil factor. Selected variables for the final analysis were CO, SO_2, black smoke, Al, Cr, Cu, Fe, Li, Mg, Ni, Pb, V and Zn.

A matrix of 38 samples and 13 variables was extracted using principal component method. Principal compo-

nents with eigenvalues over 1 were transformed by VARIMAX rotation. Three first factors explained 78% of the total variance of data. In the first factor the highest loadings were in soil markers Al, Fe and Mg, but there were very high loadings with heavy fuel oil burning markers V and Ni. The second factor had high loadings with CO, black smoke and Pb, representing traffic emissions. The third factor was highly loaded with SO_2 and Cu, possibly representing oil burning processes. Altogether, factor solution for 38 samples was unclear and difficult to interpret. The cause for poor factor analysis result was probably due to the dust episode when almost all elements reached their maximum concentrations at the same time.

To avoid the influence of dust episode, the two highest PM10 concentration days, i.e. 11 and 13 April, were removed, and a factor analysis was repeated with the remaining 36 samples (Table 3). In this case, factor solution is better and more believable. There are four factors with eigenvalue over 1 and the sum of variances is 79%. The first factor explains 33.7% of the total variance of data and Al, Mg and Fe are highly loaded, so this factor represents soil and street dust. Factor 2 accounts for 18.9% of variance and it has high loadings with CO, black smoke and Pb, which are markers for traffic exhaust. The third factor explains 17.2% of variance, and is strongly loaded with heavy fuel oil markers V, Ni and Cr. Factor 4 explains 9.1% of the total variance, and it has highest loadings with Cu and Zn. Moderately high loadings with SO_2 and V indicate that also this

Table 3
Factor analysis results with 36 days (without dust episode)

Variable	Factor 1	Factor 2	Factor 3	Factor 4
CO	0.05	**0.93**	− 0.11	0.20
SO2	− 0.23	− 0.02	0.36	0.41
Black smoke	0.26	**0.89**	0.07	0.20
Al	**0.98**	0.10	0.11	− 0.00
Cr	0.41	0.10	<u>0.62</u>	− 0.36
Cu	− 0.07	0.19	− 0.05	**0.76**
Fe	**0.98**	0.12	0.11	− 0.00
Li	− 0.03	<u>0.63</u>	− 0.11	− 0.45
Mg	**0.98**	0.11	0.07	− 0.01
Ni	0.01	0.02	**0.96**	0.09
Pb	0.15	**0.76**	0.44	0.26
V	0.28	− 0.05	**0.76**	0.42
Zn	0.19	0.23	0.33	<u>0.60</u>
Eigenvalue	4.4	2.5	2.2	1.2
Variance (%)	33.7	18.9	17.2	9.1
Source type	Soil and street	Traffic	Heavy fuel oil	Unidentified

[a]Loadings > 0.7 are in bold and > 0.5 are underlined.

fourth factor has a connection with heavy fuel oil burning processes.

3.3. Linear regression

Forward stepwise linear regression was chosen as a method. SPSS's default criteria were used in all calculations (tolerance criteria 0.0001, $p_{in} < 0.05$ and $p_{out} > 0.10$). Al was chosen as a marker for soil and street dust because it has the lowest detection limit in chemical analysis and no high loadings in other factors. There are no good elemental markers for traffic exhaust, but CO seemed to be unique and can be used as a marker (Lewis et al., 1986). The best marker for heavy fuel oil burning was Ni because there were no remarkable loadings in other factors. The most unique tracer for unidentified source (factor 4) was Cu. According to the emission inventory made in study area (Hänninen et al., 1992), wood burning is an important source of particles in Kuopio, especially in winter due to domestic heating. Soil dust and wood burning are often the only remarkable sources of potassium in many urban environments, and this was assumed to be the case in Kuopio. Lewis et al. (1986) estimated the amount of potassium in air samples, which originated from wood burning by subtracting potassium from soil away from the total potassium concentration using known K/Fe ratio in soil dust. In another study Lewis et al. (1988) used K/Fe ratio in ambient air coarse (2.5–10 μm) particle fraction as a surrogate for a ratio in soil dust. In our case the composition of soil dust was not known, but we used regression analysis to estimate potassium from wood burning. It must be noted that preliminary factor analysis gave constantly the highest loading of potassium in the soil factor without remarkable loadings in any other factor. The result of regression is presented in Table 4. Calculation of K_{wood} resulted in 8 out of 38 cases (21%) with concentration under zero. Those values were all only slightly negative, and were replaced by zero.

The results of final PM10 apportionment regression are presented in Table 5. Model 1 has been calculated using sources identified by factor analysis and model 2 includes also the wood burning tracer K_{Wood}.

All regression coefficients of tracers were significant, except Cu (factor 4), the coefficient of which was negative and non-significant (not shown). This may indicate that

Table 4
Regression equations of wood burning based potassium

Regression equation of potassium and potassium from wood burning K_{Wood} (μg m^{-3})

$$K = (0.22 \pm 0.01) \text{ Al} + (0.05 \pm 0.01)$$
$$p < 0.0000 \qquad p = 0.0003$$

$$K_{Wood} = K - 0.22\text{Al}$$

Table 5
Final apportionment models of PM10

Regression models of PM10 (μg m^{-3}) ($n = 38$)

Model 1
$$PM10 = (13.2 \pm 0.5) \text{ Al}^{***} + (5.2 \pm 1.5) \text{ CO}^{**}$$
$$+ (1524 \pm 574) \text{ Ni}^{**} + (6.4 \pm 2.1)^{**}$$
$$R^2 = 0.97$$

Model 2
$$PM10 = (13.8 \pm 0.4) \text{ Al}^{***} + (5.8 \pm 1.2) \text{ CO}^{***}$$
$$+ (987 \pm 466) \text{ Ni}^* + (65 \pm 14)K_{Wood}^{***}$$
$$+ (4.1 \pm 1.8)^*$$
$$R^2 = 0.98$$

Significance levels: $^*p < 0.05$ $^{**}p < 0.01$ $^{***}p < 0.001$

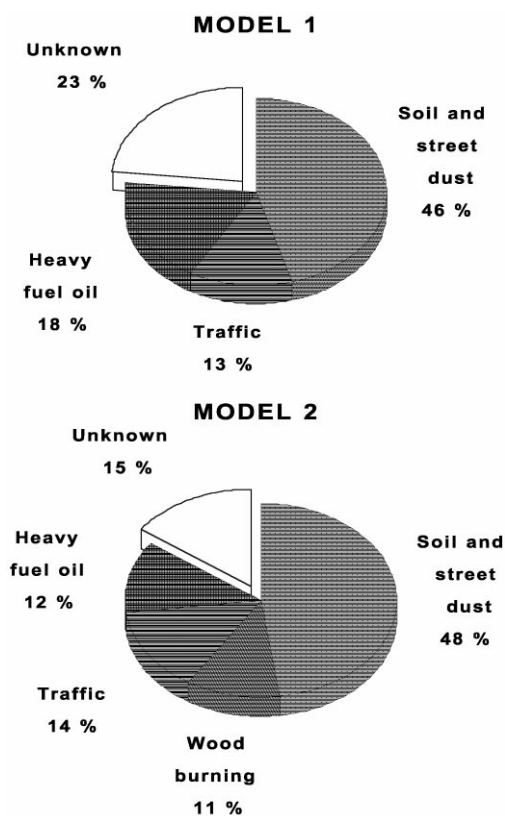Fig. 3. The source contributions to the mean PM10 (27.2 μg m^{-3}) in the study period. Model 1 with the sources identified by the factor analysis. Model 2 includes also wood burning.

source emitting copper was included in the other source groups in the model.

The source contributions to the mean PM10 concentration 27.2 μg m^{-3} are presented in Fig. 3. Soil and street dust represents 46–48%, traffic 13–14%, heavy fuel
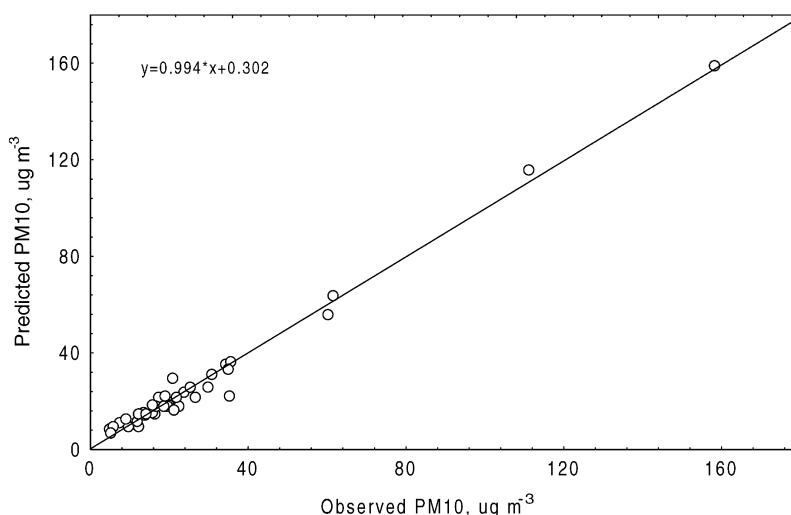
Fig. 4. Predicted vs. observed PM10.

oil 12–18% and wood burning ca. 11% from the mean concentration and the proportion from unidentified sources is 15–23%. Fig. 4 displays scatterplot of predicted vs. observed values of PM10 in 38 days. The data points with high concentrations have no major influence on the regression slope. There are two outliers in the middle range of data having standard residuals − 2.11 and 3.36. One is located above and the other below the regression line at about the same distance from the line, nullifying the effect of each other. The residuals in the final model were nearly normally distributed. Therefore log transformations were not performed.

The stability of regression solution for the change of marker elements were tested using Fe and Mg instead of Al as a marker for soil dust. The coefficients of the markers did not change considerably, and their 95% confidence intervals were overlapping.

The source contributions from the full measuring period are strongly emphasized by dust episode. When the period was divided in two separate parts, winter (8 February–17 March) and spring (21 March–26 April), and the contributions were recalculated, the effect of seasonal variation was seen more clearly. The winter period had the mean PM10 concentration 17.1 $\mu g\,m^{-3}$ and the contributions were 23% (4.0 $\mu g\,m^{-3}$) from soil source, 25% (4.2 $\mu g\,m^{-3}$) from traffic, 18% (3.1 $\mu g\,m^{-3}$) from heavy fuel oil combustion, 15% (2.6 $\mu g\,m^{-3}$) from wood burning, and 19% (3.3 $\mu g\,m^{-3}$) from unidentified sources. The mean PM10 in the spring period was 44.3 $\mu g\,m^{-3}$, and the respective contributions were 64% (28.5 $\mu g\,m^{-3}$) from soil, 6% (2.8 $\mu g\,m^{-3}$) from traffic, 8% (3.6 $\mu g\,m^{-3}$) from heavy fuel oil combustion, 10% (4.3 $\mu g\,m^{-3}$) from wood combustion, and 12% (5.1 $\mu g\,m^{-3}$) from unidentified sources.
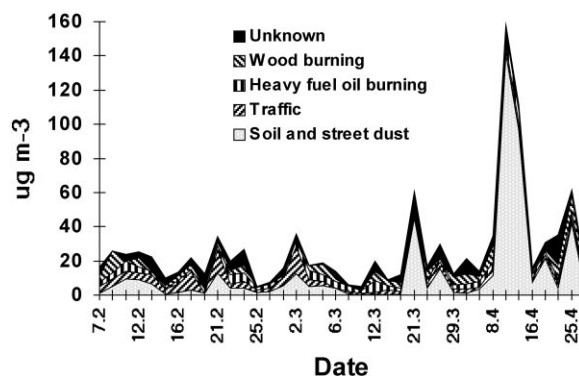

Fig. 5. Daily source contributions of different sources estimated by model 2.

The daily source contributions of PM10 are possible to estimate by setting the daily tracer concentrations of each source to the regression equation. It must be kept in mind that this kind of single tracer method is more sensitive to errors in data than methods which use several markers per source (as CMB). Fig. 5 shows the estimated daily source contributions. Soil and street dust is the main source during dust episode, but burning processes and traffic dominate during winter months.

4. Discussion

Henry (1987) has strongly criticized the use of factor analysis as a quantitative receptor modeling method. However, FA-MLR uses factor analysis only as

a qualitative method for describing the data. Ito et al. (1986) have investigated the sensitivity of qualitative factor analysis as a part of FA-MLR method. Random errors up to 30% had no significant qualitative impact on factor analysis solutions. Reducing number of samples from 70 to 35 caused more inaccuracies in the interpretation of the factors. However, the requirement for minimum number of samples according to Henry et al. (1984) seems to be reliable. Number of samples and variables in this study meet those requirements.

Factor analysis of 38 days' data was misleading because of the impact of a dust episode. High concentrations of many marker elements during these two days caused strong "source independent" variation, and factor analysis interpreted most elements to originate from the same source. When factor analysis was carried out without dust episode days, the results were more reliable. Nevertheless, the meaning of factor 4, which was strongly loaded with Cu and also with Zn, V and SO_2, remained unclear. The use of 36 samples instead of 38 samples in the factor analysis is justified, because the purpose of the factor analysis is only to produce a qualitative portrait on the source situation in the study area. This is especially the case in this kind of studies with limited number of samples. The regression analysis can thus be conducted with all 38 samples, because it can be treated as an independent step in the receptor modeling procedure.

Al appears to be the best tracer for soil and street dust in airshed of the study area, but Fe and Mg are potential options. Because the ground was covered by snow until early April, the main wintertime sources of Al were streets, which were sanded to prevent slipping.

Finding a marker element for traffic exhaust has been a problem in many receptor modeling studies over the past few years because of the use of unleaded fuel. However, Lewis et al. (1986) showed in their Denver study that CO is equivalent to fine particle Pb as a tracer of primary motor vehicle emissions. The measuring site in Kuopio was located so close to the center of town that the main source of CO is traffic. There was still quite high loading of Pb (0.76) in a traffic factor although selling of leaded gasoline had ended four months before the beginning of this study. This could have been a consequence of lead that was still in oils, exhaust pipes, and fuel systems. Pb was, however, not sufficient for regression because of high loading in the heavy fuel oil burning factor.

The relation of heavy fuel oil and wood burning is interesting in Kuopio. In model 1 the proportion of heavy fuel oil burning is 18%, but in model 2 with wood burning, it is only 12% (Fig. 3). Approximately 2 km East from the measuring site (see Fig. 1) is located a chipboard factory, which co-combusts waste wood, waste hydraulic oil, and heavy fuel oil. The factory lacks emission control systems, and particle emissions are strongly dependent on combustion conditions. On the basis of manufacturer's specifications, waste hydraulic oil contains re-

markable amounts of Zn and also small amounts of Cu. Because factor 4 was loaded with Cu and Zn, it is probable that this factor represents, at least partly, co-combustion of heavy fuel oil, hydraulic oil and waste wood at this factory. This kind of mixed fuel source gives contribution to both vanadium- and potassium-related sources and can affect the proportions of both of them. This may also explain the negative regression coefficient of Cu because the source emits both vanadium and potassium. Validation of this suggestion would need further source sampling and analysis.

It is unresolved why factor analysis found potassium only in the soil factor. One explanation may lie in the fact that we had limited number of cases available, which restricts the accuracy of analysis. To have more information about the nature of wood burning, we conducted factor analysis with K_{wood}, and it loaded strongly in the same factor with Cu and Zn. This result supports our previous theory about burning of mixed fuels in Kuopio.

Unidentified sources were responsible for at least 15% of PM10 particles. Traditionally SO_4^{2-} has been a tracer for long-range transported particles and secondary particles, but unfortunately ions were not analyzed in this study. Based on neural network analysis of Ruuskanen et al. (1995), the long-range transport can be a significant source of air pollutants in Kuopio. Morandi et al. (1987) in New Jersey, USA, and Okamoto et al. (1990) in Tokyo, Japan, have reported secondary aerosol contributions to be 48% and 30%, respectively. Because of remote location of Kuopio the contribution of long-range transport is assumed to be lower. Long-range transport can also be partly included into the heavy fuel oil contribution, because nickel often correlates with SO_4^{2-} and other secondary particle related elements.

5. Conclusions

A receptor modeling study was carried out in Kuopio, Finland, as part of a health impact study of air pollutants to produce both qualitative and quantitative information on sources of PM10 particles during the period February–April, 1994. Factor analysis followed by multiple linear regression was used as a method, and the main sources and their contributions to the mean PM10 concentrations were estimated. Soil-based material was found to contribute almost half of the PM10 during the study period. Heavy fuel oil burning, traffic exhaust and wood burning were the other identified sources.

The reliability of factor analysis was found poor when the data included resuspended dust days with extremely high PM10 concentrations. On those days, most markers reached their maximum levels, which led to false analysis result. In the case of potassium, regression analysis was able to produce reduced marker for wood burning. Carbon monoxide was the best independent marker for

traffic, and on the basis of this study, it can be used as a marker for gasoline- and diesel-powered vehicles instead of Pb or Br, especially in the centers of cities. Co-combustion of heavy fuel oil, waste wood and hydraulic oil in chipboard factory in a distance of about 1.5 km from measuring site was identified as a probable reason for the connection between wood burning and heavy fuel oil burning particles.

As a conclusion, dust episodes cause special requirements for interpretation of results from multivariate receptor models. Another important result of this study was a recognition of effect of co-combustion of wood and waste residual oil. Although factor analysis did not identify clear factor for wood burning, it was possible to estimate the quantity of particles from wood burning because local emissions were known. Thus, good knowledge of local conditions (sources, climate) is important, and it must be taken into account in every stage of modeling. The next step in specifying the source contributions in Kuopio could be source sampling to achieve the local source profiles and then use CMB in source apportionment.

Acknowledgements

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